Aggregated Load Scheduling for Residential Multi-Class Appliances: Peak Demand Reduction

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***Abstract*—The Smart Grid represents an unprecedented opportunity to move the energy industry into a new era. In this context, Demand Response programs provide mechanisms to regulate the power demand through load control according to conditions of the supply side, where consumers can efficiently schedule the operation of their appliances. This paper has proposed an efficient local load scheduling strategy for residential multi-class multi-constraint appliances by shifting and interrupting load requests to flatten the aggregated consumption. One scenario for each smart house, including the desirable usage schedule of its appliances in a 24-hour period, is considered. The proposed strategy has supposed a time-independent constant electricity consumption threshold, imposed by the grid stability management, in each time interval. The demand response system attempts to optimally schedule the received load requests over time, aiming at flattening the aggregated consumption meanwhile, maximizing satisfaction of consumers. The results have indicated that decreasing the electricity consumption threshold up to 60% of the maximum peak demand results in significant aggregated consumption flattening and also admissible appliance reception delay.**

***Index Terms*—Smart Grid, Supply and Demand, Load Management, Scheduling.**

I. INTRODUCTION

The Smart Grid defines an electricity network that can intelligently integrate the behaviors and actions of generators and consumers, in order to efficiently deliver sustainable, economic, and secure electricity supply [1]. Demand Response (DR) has been thought as a key component in the smart grid which allows electricity consumers to adapt their electricity consumption according to fluctuations in the electricity generation over time. DR technologies facilitate communication between energy utilities and smart appliances at the customer premises, which are indispensable for consumers' ability to reduce or to shift their power consumption during peak demand periods [2], [3].

Consumers become secondary actors in the electricity wholesale market dynamics through DR programs [4]. Load control actions are leveraged by market actors such as aggregators that offer specific load reductions in the market. Participants of DR programs have the opportunity to help those to reduce the risk of power grid outages thus provide a value to the Distribution System Operator (DSO).

This paper critically discusses the *Peak Demand Reduction* problem based on the *Appliance Reception Minimization* method. First, a DR model for smart houses, where the DR System (DRS) receives and schedules a large number of consumers' partial load requests, is proposed. The advantage of this approach is its ability to streamline the control of received load requests while optimally schedule them in each time interval by decreasing the peak-to-average ratio. Furthermore, an efficient local load scheduling strategy for smart houses has been proposed to shift or to interrupt demands to flatten the aggregated consumption, where each smart house has a desired usage scenario of its appliances. When consumers provide their appliances to the DRS in the "DR Ready" mode, they give permission to the DRS to schedule their multi-class multi-constraint appliances in a 24-hour period restricting with a specific deadline flexibility for completion of each appliance in a worst case.

So far, however, there has been little discussion about coupling *Electricity Consumption Threshold (ECT)* provided by the DSO grid stability management with DR programs preventing appliances of smart houses to start at their desired time. This paper follows a case-study design that appropriately utilizes the time-independent *ECT* constraint to schedule the received load requests of appliances of smart houses in each time interval. Although consumers provide flexibility to the DRS, they are not interested in waiting too long to receive their appliances in completed state. Hence, the proposed aggregated local load scheduling technique for residential appliances aims at *maximizing satisfaction of consumers* while considering *ECT*. Here, *local* means receiving load requests in specific time intervals and scheduling them in these intervals.

The remainder of paper is organized as follows: Section II reviews related work. Section III presents descriptions of the system model and scenarios of smart houses. Section IV clarifies the proposed local load scheduling algorithm with its relevant sub-procedures. Section V demonstrates an experimental setup and the obtained results with their evaluations. Finally, conclusion and future work are provided in Section VI.

II. RELATED WORK

In recent years, there has been an increasing amount of literature on incentivizing consumers to shift their electricity consumption by varying the electricity prices [5], [6]. Sou *et al.* [5] investigated the minimization of electricity bills combined with enforcing uninterruptible and sequential operation model constraints. Nonetheless, the utilized mixed integer linear programming approach to solve the scheduling problem is not scalable and the appliance classification is limited to the interruptibility feature. In addition, [6] has proposed an electricity load scheduling algorithm that controls the operation time and energy consumption of appliances based on adapting time-of-use pricing to minimize the total electricity bill. A serious weakness with this argument, however, is that the authors have used only one smart house as test-bed, excluding any aggregated consumption threshold.

On the other hand, a solution to the problem of optimally scheduling a set of residential appliances under day-ahead variable peak pricing scheme has been studied in [7]. Here, the objectives are minimizing the electricity bills and spreading the electricity usage out in each time interval simultaneously. On the contrary, they have only considered a limited number of appliances. Finally, the focus in [8] is on applying the appliance priority-based methodology to quantify consumers' preferences for using appliances during peak times based on the Knapsack problem approach. Nonetheless, in the proposed mechanism, there is no consumption threshold constraint to prevent consumers from exceeding it.

III. SYSTEM MODEL

Smart houses play a critical role in DR programs [9]. When the consumer of a smart house operates his appliances in the "DR ready" mode, he offers flexibility to the grid and permits the DRS to take control of his appliances. In this paper, it is assumed that there are $N \in \mathbb{N}$ smart houses, where each smart house $H_i, i \in (1,2,\dots,N)$, has $A \in \mathbb{N}$ appliances. Furthermore, $x_{i,j}^t \in \{0,1\}$ denotes the decision variable of the DRS that whether allows j^{th} appliance of i^{th} smart house to start or to continue its work in time interval t or not. In the following, the objective function and relevant constraints of the proposed system model will be clarified.

A. Objective function

Consumers may give priorities to their appliances based on their preferences [8]. More accurately, a time-independent constant pairwise priority exists between two distinct types of appliances based on some criteria, e.g., emergent usage, welfare, or electricity cost. Consumers provide their normalized priority vector to the DRS by using their own pairwise comparisons. The priority vector of i^{th} smart house, PV_i, includes A elements, in which its each element $0 < p_{i,j} \leq 1$ refers to the priority of j^{th} appliance of that smart house. Since PV_i is normalized, the sum of its elements should be equal to one. The DRS employs the provided priority vectors to qualify for permitting corresponding appliances of received load requests to start or to continue in each time interval. In this paper, the comparison criterion is the emergent usage. Even though consumers permit the DRS to schedule their appliances, however, they hope to receive their appliances in the completed state at when they desire. Equation (1) formulates this objective:

$$f(t) = max \sum_{i=1}^{N} \sum_{j=1}^{A} \left(x_{i,j}^t \times p_{i,j} \right). \tag{1}$$

B. Constraints

Appliance full operation: Appliances are drivers of electricity demands in each smart house. The electricity consumption of j^{th} appliance of i^{th} smart house in time interval t is $EC_{i,j}^t \in \mathbb{R}_0^+$ (watt). It should be noted that $TEC_{i,j} \in \mathbb{R}^+$ is its total electricity consumption in a 24-hour period. To guarantee the full operation of appliances, the DRS checks whether each appliance has completed its duty during the day defined by last time interval of the day T. Hence, (2) is imposed to satisfy this hard constraint:

$$\sum_{t=1}^{T} \left(EC_{i,j}^t \times x_{i,j}^t \right) = TEC_{i,j}. \tag{2}$$

Smart features: Appliances are divisible based on some smart features. Fig. 1 pictures classification of appliances coupling with correspondent examples. Firstly, appliances have been classified according to the *shiftability* feature [10]. Shiftability is to give permission to the DRS to shift load requests of *shiftable appliances* to another time interval. On the other hand, load requests of some appliances, such as the refrigerator, cannot be shifted. Thus, those applainces become members of *non-shiftable appliances*. Secondly, the shiftable appliances can be divided into two groups based on the *interruptibility* feature. The electric vehicle is an example of this feature, where the DRS can both shift and interrupt the duty cycle of charging the electric vehicle. Nevertheless, those appliances which are shiftable but uninterruptible are called *uninterruptible appliances* (e.g., the dish washer). Consequently, the DRS should give consideration to when it receives an uninterruptible load request in t^{th} time interval, it should check whether the relevant appliance has been allowed to start or to continue its work in the $(t-1)^{th}$ time interval. If so, the DRS cannot interrupt and shift it to another time interval. Equation (3) is a hard constraint and belongs to only uninterruptible appliances:

$$\begin{cases} x_{i,j}^t = 1, & x_{i,j}^{t-1} = 1, \\ x_{i,j}^t \in \{0,1\}, & otherwise. \end{cases} \tag{3}$$

Appliance dependency: In practice, there are some *dependency* relationships between consumption activities of some appliances of each smart house [2]. These relationships impose a hard constraint on the DRS that must be satisfied entirely. Dependency is denoted by the relationship between two different appliances. For instance, it is infeasible to put clothes into laundry dryer before washing them. More accurately, these dependencies can be divided into two independent groups named *consecutive* or *concurrent* dependencies. The former group relates to those appliances which cannot be used at the same time, as exemplified before. Alternatively, concurrent dependency refers to operations which should be performed simultaneously (e.g., lighting and

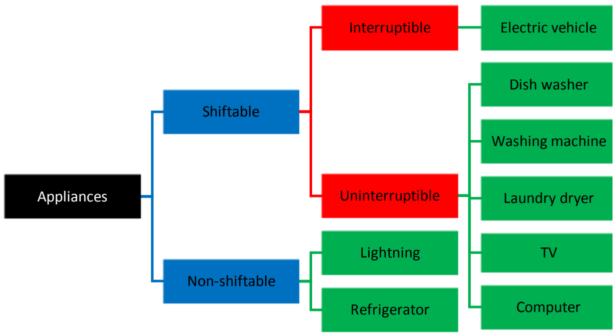

Figure 1. Classification of appliances

watching TV). $D_{i,j,k} \in \{0,1,2\}$, in which $\{j,k\} \in (1,2,\dots,A)$, corresponds to dependency value between appliances j and k of smart house i. If it is zero, there is no dependency between the relevant appliances. If $D_{i,j,k}$ is equivalent to one, there is a consecutive dependency relationship. Here, if appliance k finishes its duty until time interval $t-1$, then, appliance j can be whether allowed to start or to continue from time interval t. Finally, if the dependency value is equal to two, there is a concurrent dependency. In this situation, appliance j can be allowed to start or to continue if appliance k is allowed to start or to continue in the same time interval. Equation (4) demonstrates the dependency constraint:

$$\begin{cases} x_{i,j}^{t} \in \{0,1\}, & \exists k \rightarrow \left(\left(D_{i,j,k}=1\right) \wedge \left(\sum_{h=1}^{t-1} \left(EC_{i,k}^{h} \times x_{i,k}^{h}\right) = TEC_{i,k} \right) \right), \\ x_{i,j}^{t} \in \{0,1\}, & \exists k \rightarrow \left(\left(D_{i,j,k}=2\right) \wedge \left(x_{i,k}^{t}=1\right) \right). \end{cases} \quad (4)$$

Deadline flexibility: As mentioned previously, consumers put their appliances in the "DR Ready" mode to be scheduled by the DRS. In addition, they provide a particular time-oriented hard *deadline flexibility* constraint of each appliance to the DRS. With respect to the load profile of each appliance, the required completion time period of each appliance is known to consumers. For instance, one consumer desires to charge the electric vehicle from 18:00 to 20:00. Nevertheless, one may provide two hours flexibility of the electric vehicle to the DRS. The provided deadline flexibility means that one can wait at most two additional hours to receive the charged electric vehicle. This flexibility is applicable to both start and finish times of appliance operation, since the DRS can shift the starting time, however, it should finish the appliance operation at latest at the provided flexibility. This kind of flexibility facilitates the DRS by shifting or even by interrupting appliances. The DRS considers the time difference between the provided deadline flexibility of each appliance and current time interval before shifting it to another one. Equation (5) indicates this hard constraint:

$$RL_{i,j}^{t} \leq \left(DF_{i,j} - t\right). \quad (5)$$

$RL_{i,j}^{t} \in \mathbb{Z}^{*}$ relates to the total remaining loads of j^{th} appliance of i^{th} smart house from t^{th} interval until end of its cycle. $DF_{i,j}$ (time instant) denotes the provided deadline flexibility of that specific appliance. The DRS examines each of the received load requests for satisfying this constraint. If the total remaining loads of an appliance is still less than the time difference between the provided deadline flexibility and current time interval t, then, the DRS can decide to whether allow it to start or to continue in current time interval or shift it to another time interval.

Aggregated consumption threshold: Many electricity producers are experiencing a deficit of electricity generation capacity in consequence of load requests by consumers. More accurately, the generated amount of electricity is often unable to satisfy the requested loads in a specific time interval. Hence, the DSO currently applies an $ECT \in \mathbb{R}^{+}$, to ease grid stability [11]. ECT (watt) is a soft constant over the time intervals, in which it sometimes cannot be satisfied due to the provided deadline flexibilities and uninterruptibility feature of some appliances. Therefore, the DRS can only apply this constraint on the remaining shiftable loads including those which: I) have not started yet, and II) have started earlier but corresponding appliances are interruptible. This threshold, as formulated in (6), attempts to keep the aggregated consumption of allowed load requests in each time interval under the provided ECT:

$$\sum_{i=1}^{N} \sum_{j=1}^{A} \left(EC_{i,j}^{t} \times x_{i,j}^{t}\right) \leq ECT. \quad (6)$$

C. *Scenario*

Each smart house H_i has a specific scenario including usage pattern of its appliances. The DRS is unaware of the scenario details of all smart houses before scheduling and it continuously receives load requests over time. Table I exhibits a sample scenario including the desired schedule of appliances of a smart house.

TABLE 1. A SAMPLE SCENARIO OF A SMART HOUSE

Start	End	Activity description	Deadline	Dependency	Priority
00:00	24:00	Using the refrigerator.	24:00	--	Infinite
08:00	24:00	Turning the lights on.	24:00	--	Infinite
08:05	09:50	Using the dish washer.	10:30	--	0.2158
08:40	10:00	Using the washing machine.	10:30	--	0.1063
11:00	11:50	Using the laundry dryer.	12:30	Washing machine	0.1499
11:30	22:40	Using the computer.	23:30	Lightning	0.2649
19:50	22:00	Watching the TV.	24:00	Lightning	0.1293
20:00	22:00	Charging the electric vehicle.	24:00	--	0.1338

For instance, the consumer of the smart house provides two hours of deadline flexibility to the DRS from charging the electric vehicle. The DRS receives the first load request of the electric vehicle at 20:00. Therefore, the DRS has an opportunity to deliver the charged electric vehicle until 24:00 by shifting and interrupting the charging procedure, since the electric vehicle is a member of the interruptible appliances. Furthermore, there is a consecutive dependency between the laundry dryer and the washing machine. Moreover, a concurrent dependency exists between the personal computer (or the television) and the lighting system. Furthermore, it is worthwhile to note only shiftable appliances have priority among each other. Hence, the refrigerator and lighting will not undergo any scheduling procedure, since they are members of the non-shiftable appliances. Therefore, they receive infinite priority.

IV. LOCAL LOAD SCHEDULING OPTIMIZATION ALGORITHM

The DRS continuously applies the load scheduling optimization algorithm on the received load requests to produce a specific schedule for appliances of each smart house based on the aforementioned objective and constraints in each time interval. Apart from *ECT*, the DRS permits the non-shiftable loads to do their duty over time. Furthermore, if there are uninterruptible appliances which have started in the previous time interval, they should be granted to continue. Finally, if there would be a load, where shifting it to the next time interval will exceed its provided deadline flexibility, again, it should be permitted to start or to continue. After completing these procedures, the scheduling algorithm will check whether total consumption of the remaining loads is below than the remaining *ECT*. If so, all will be allowed to start or to continue their procedure. Otherwise, the algorithm calls the Knapsack procedure to permit a subset of loads from the remaining ones to start or to continue, and to shift the unpermitted loads to the next time interval.

A. The Knapsack Problem

The Knapsack problem is a traditional problem of Computer Science in combinatorial optimization literature [12]. Given M items, the Knapsack packs the items to get the maximum total value, where each indivisible item has a weight and a value. The total weight that can be carried, is fixed by the Knapsack capacity. The Knapsack problem is an NP-Complete problem since the time complexity of solving it in a brute-force manner is $O(2^M)$. This method calculates all feasible subsets in order to find the optimal one. In the load scheduling problem, the priority of corresponding appliances of the remaining loads matches with the items in the Knapsack problem. In addition, weights correspond to the electricity consumption of the remaining loads. The objective in the Knapsack problem is to maximize the total value, whereas in the load scheduling problem, the objective is to maximize the total number of allowed loads. Finally, the Knapsack capacity corresponds to the remaining *ECT*. In the load scheduling problem, the DRS should select and allow those loads which optimize the objective and satisfy the constraints thoroughly. In summary, the Knapsack problem is reducible to the load scheduling problem. As a result, the load scheduling problem is also an NP-Complete problem.

The Knapsack procedure receives the remaining loads and calculates the fitness of produced feasible subsets, where each subset comprises some loads. In conclusion, the outcome of this approach is a subset of remaining loads which should be allowed to start or to continue in this time interval. Obviously, there will probably be some loads which are not permitted to start or to continue. Therefore, these loads should be shifted to the next time interval. However, in order to decrease the time complexity, dynamic programming approach has been applied to solve the Knapsack problem, whenever it is required [7], [8]. Algorithm 1 describes the procedure of the proposed local load scheduling optimization algorithm.

V. EXPERIMENTAL SETUP AND ANALYSIS

This section, first describes the experimental setup including analysis criterion, and data types. Subsequently, the experimental results will be clarified precisely.

Inputs : Scenarios, flexibilities, classification of appliances, *ECT*.
Output: Schedule of appliances of all smart houses.

Preprocessing the input data;
While *receiving load requests in specific intervals* **do**
  Start or continue the non-shiftable loads;
  Continue uninterruptible loads, which have started previously;
  Start or continue loads which cannot be shifted or interrupted anymore due to their provided deadline flexibility;
  If *there are some remaining loads* **then**
    If *their total consumption is less than the remaining ECT* **then**
      Allow them to start or to continue;
    Else
      Call the Knapsack procedure, allow the output loads to start or or to continue, and Shift unpermitted loads to the next interval;
    End
  End
End

Algorithm 1. Pseudo code of the local load scheduling optimization algorithm

A. Experimental Setup

The proposed algorithm has been implemented with MATLAB® R2014b on a computer with an Intel Core i7 2.0 GHz CPU, and 6 GB of memory. Load profiles of appliances, shown in Fig. 1, have been captured from the TraceBase open repository which comprises electrical appliance power traces [13]. To simplify the experiments, consumers will use their appliances once a day. Furthermore, usage occurrence of appliances, their deadline flexibility, and priority have been randomly selected. The DRS continuously receives load requests of $N = 100$ smart houses in 5-minutes time intervals over a 24-hour period. Each load request only includes its required electricity consumption for the next five minutes except the first one, which additionally comprises its shiftability and interruptibility memberships, priority, deadline flexibility, and dependency status.

The results will be analyzed based on variations of *ECT*. *ECT* is constant over time and will be 20%, 40%, 60%, or 80% of the maximum aggregated consumption of all smart houses at peak time interval. It is beneficial to note that although the DRS is unaware of all scenarios prior to starting the schedule, however, the DSO grid stability management informs the DRS about *ECT* based on the forecasted or learnt scenarios of previous days. If *ECT* equals to or is greater than the maximum peak demand, no scheduling is needed. Hereinafter, each *ECT* percentage is based on the informed maximum peak demand.

B. Experimental Results

Fig. 2 depicts the scheduled aggregated consumption of 100 scenarios with respect to the changes in *ECT*. The period from 10:45 to 00:45, in which the aggregated consumption approaches *ECT*, is selected. The peak electricity consumption equals to almost 289 kW at 20:30, when *ECT* is 100%. In addition, the average aggregated consumption is almost 56 kW in a 24-hour day. The DRS desires to reach a point, in which there are as few peak times as possible. More in details, as Fig. 2 proves, when *ECT* is 20%, the scheduler has been successfully flattened the aggregated consumption between

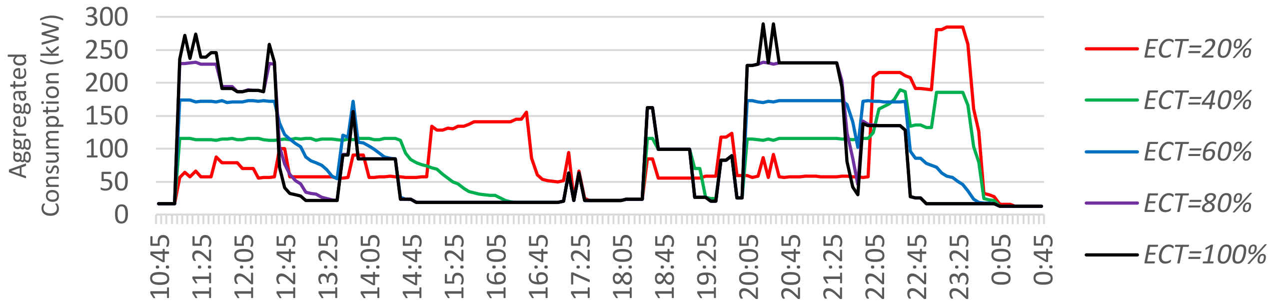

Figure 2. Aggregated consumption of 100 scenarios with respect to changes in *ECT*

10:45 to almost 14:30. However, this flattening causes another peak period from around 14:45 to 16:45. The reasons are the uninterruptibility feature and deadline flexibility of some appliances. This is also true for the future time intervals. Furthermore, when *ECT* is low (20%), the Knapsack cannot find any solution for the remaining loads in some time intervals due to the low remaining *ECT*. Consequently, the DRS has to shift all the remaining loads to the next time interval. According to the deadline flexibility constraint, the DRS must allow some loads to start or to continue their operation apart from the remaining *ECT* in the next time intervals. As a result, this produces another peak time. By applying this threshold (20%), electricity consumption at the peak time (almost 284 kW) decreases only 1.73% comparing with the maximum peak demand (almost 289 kW).

Nonetheless, when *ECT* is 40%, the Knapsack procedure can permit most of loads to start or to continue their work in corresponding time interval, and accordingly, the DRS should shift only a few remaining loads to the next interval. It will decrease the aggregated consumption at peak times (almost 189.4 kW) and flatten the aggregated consumption by 34.46%, as represented in Fig. 2. In addition, if *ECT* increases up to 60%, the peak reduction ratio will be 40%. Ultimately, no significant achievement was found from increasing *ECT* to 80%. The reason is that most of load requests are permitted to start or to continue their operation at the time they request. In this situation, the peak reduction ratio is only 20.17%.

Table II analysis the number of referrals to the Knapsack procedure (*K-Referrals*), average deviation between appliance deliverance and reception times (*T-Deviation*), maximum required *ECT* (*M-ECT*), and peak-to-average ratio (*PAR*).

TABLE II. ALGORITHM ANALYSIS BASED ON ECT VIOLATION

	ECT violation				
	57.8 kW (20%)	115.6 kW (40%)	173.4 kW (60%)	231.2 kW (80%)	289 kW (100%)
K-Referrals	56	68	48	12	0
T-Deviation	220	115	30	5	0
M-ECT	284 kW	189.4 kW	173.4 kW	231.1 kW	289 kW
PAR	5.07	3.38	3.09	4.12	5.16

According to *K-Referrals*, if *ECT* equals to 20%, the Knapsack procedure will be called for 56 times during the whole schedule. This number will be raised if *ECT* increases up to 40%. The reason is the existence of some intervals that the DRS allows some shiftable and interruptible loads to start or to continue their operation. Furthermore, there will be some new load requests in the next time intervals. Hence, the aggregated consumption of new and shifted load requests will be more than the remaining *ECT* and the number of referrals to the Knapsack procedure increase. Nevertheless, this number will decrease when *ECT* is equal to 60%. The reason is the large number of load requests that can be allowed to start or to continue in each time interval with respect to the assigned *ECT*. In addition, some of these permitted to start or to continue loads are members of the uninterruptible appliances. Hence, in the next time intervals, apart from the remaining *ECT*, they must be allowed to continue their duty. Therefore, the number of referrals to the Knapsack procedure will decrease. This is also applicable when *ECT* is 80%. Obviously, there is no need to call the Knapsack procedure when the assigned *ECT* is 100%.

Considering the *T-Deviation* values in Table II, the DRS has the opportunity to shift and interrupt some loads to satisfy the constraints based on the provided deadline flexibilities of appliances. Hence, some consumers will confront reception delay of their appliances. For instance, although one consumer desires to receive his charged electric vehicle at 18:00, however, he has provided two hours flexibility to the system. It means that he can receive it in worst case at 20:00. Now, after finishing the scheduling, the consumer observes that he receives the charged electric vehicle at 18:45. Therefore, there is 45 minutes reception delay. As a result, according to Table II, consumers will averagely receive all of their appliances in the completed status with 220 minutes delay. This average delay decreases when *ECT* increases. The fact is that appliances will be permitted to start their operation at the time they request. Most delays are related to the electric vehicle since it is a member of the interruptible appliances.

With respect to Table II, maximum needed *ECT* (*M-ECT*) denotes the aggregated consumption at the peak time, when *ECT* changes. What is interesting is that if assigned *ECT* is 60%, the corresponding *M-ECT* is less than the assigned *ECT* (173.4 kW). It means that the DRS is entirely successful in flattening the aggregated consumption, even below the assigned threshold. Nevertheless, this is not feasible about the solutions when *ECT* is equal to 20% or to 40%. The DRS in these two circumstances has to exceed the assigned threshold since it should allow the non-shiftable and uninterruptible loads to continue their work apart from the remaining *ECT*. Furthermore, since the *T-Deviation* is not averagely too high when *ECT* is 60%, it is not mandatory to assign a higher threshold, e.g., 80%. Accordingly, the value of peak-to-average ratio (*PAR*) decreases, when *ECT* is up to 60%.

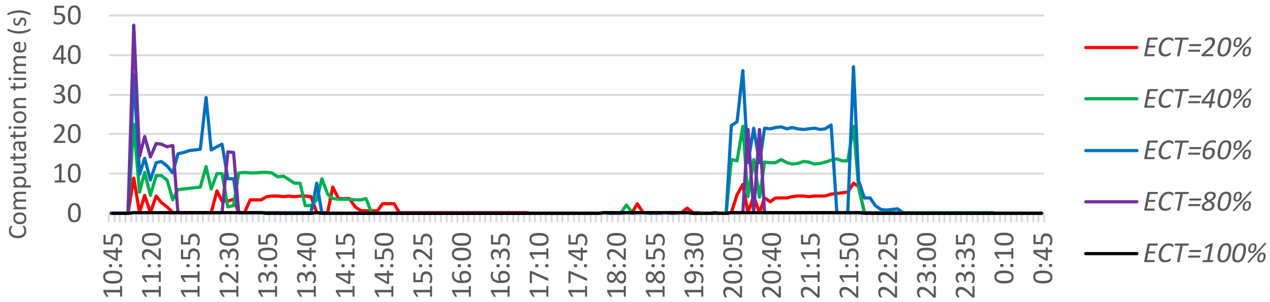

Figure 3. Computation time of running the algorithm with respect to changes in *ECT*

As the final analysis, Fig. 3 demonstrates more time complexity when the assigned *ECT* increases. Nonetheless, number of time intervals, in which the Knapsack procedure should run, decreases. Having some uninterruptible appliances and the deadline flexibility constraint are reasons of this decrease. If the DRS allows uninterruptible loads to start in a time interval, it has to shift more loads since the remaining *ECT* has decreased. These shifted loads will be accumulated and eventually the Knapsack procedure confronts a large number of remaining loads in a time interval. As a final note for this analysis, running the local load scheduling algorithm employs only 5% of CPU bandwidth with almost 350 megabytes of memory, when *ECT* is 20% to 80%. Obviously, there is no influential computation time when *ECT* is 100%.

VI. Conclusion and Future Work

In this paper, load requests of smart house appliances are scheduled by a Demand Response System (DRS) that runs as a centralized control by e.g., an aggregator actor in the electricity market. Based on this control, this paper has investigated a DR strategy incorporating a local load scheduling optimization algorithm. Each consumer provides a daily scenario describing his appliance usage pattern. Appliances of each smart house are classified based on the shiftability feature. Those appliances that can be shifted to other time intervals have further divided based on the interruptibility feature. Each shiftable appliance has a hard deadline flexibility constraint provided by the consumer. Furthermore, some appliances have concurrent or consecutive dependency relationships among themselves imposing a hard constraint on the DRS in scheduling. Consequently, a local load scheduling algorithm based on the Knapsack concept for solving the scheduling problem has been proposed. The Knapsack procedure attempts to select a subset of remaining loads to permit them to start or to continue, and shift the others in some time intervals. The main objective applied in this algorithm is maximizing satisfaction of consumers while aiming at peak demand reduction. Results considering an aggregation of 100 smart houses, have shown that the application of an electricity consumption threshold results in flattening of the aggregated consumption and leads to a decreased peak demand. As future work, we are planning to apply learning and forecasting approaches to enhance the load scheduling strategy while improving the system model by utilizing multi-objective optimization techniques in order to incentivize consumers to actively participate in DR programs.

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